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Transient ischemic attack analysis through non-contact approaches

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Abstract

The transient ischemic attack (TIA) is a kind of sudden disease, which has the characteristics of short duration and high frequency. Since most patients can return to normal after the onset of the disease, it is often neglected. Medical research has proved that patients are prone to stroke in a relatively short time after the transient ischemic attacks. Therefore, it is extremely important to effectively monitor transient ischemic attack, especially for elderly people living alone. At present, video monitoring and wearing sensors are generally used to monitor transient ischemic attacks, but these methods have certain disadvantages. In order to more conveniently and accurately monitor transient ischemic attack in the indoor environment and improve risk management of stroke, this paper uses a microwave sensing platform working in C-Band (4.0 GHz–8.0 GHz) to monitor in a non-contact way. The platform first collects data, then preprocesses the data, and finally uses principal component analysis to reduce the dimension of the data. Two machine learning algorithms support vector machine (SVM) and random forest (RF) are used to establish prediction models respectively. The experimental results show that the accuracy of SVM and RF approaches are 97.3% and 98.7%, respectively; indicating that the scheme described in this paper is feasible and reliable.

Keywords: Transient ischemic attack, Internet of things, Microwave sensing platform, Machine learning, Artificial intelligence

Introduction

Transient ischemic attack (TIA) is a transient neurological disorder caused by focal ischemia of the brain or retina without acute infarction. The clinical symptoms usually last less than 1 hour and the neurological function can return to normal after the onset [1]. TIA is characterized by sudden onset, short duration and high frequency of attack. Currently, the causes of TIA are generally recognized by the medical community as follows :(1) Embolus in arterial blood flows into the brain, resulting in blockage and poor circulation of blood. (2) When blood pressure fluctuates, especially when blood pressure drops, the blood flow in the distal part of the brain's smaller blood vessels decreases. (3) Changes in blood composition cause blood clots to form in blood vessels, which can block blood vessels in the brain [2] [3]. Relevant clinical experimental data show that TIA has an early warning effect on stroke. After TIA, the incidence of stroke within 48 h is as high as 50%, and the incidence of stroke within 3 months is 10%–20% [4]. Every year, there are many old people living alone in the world who do not receive effective attention and timely treatment when suffering from TIA, resulting in a subsequent stroke or even death. Some literatures also give other aspects of TIA [5–7], indicating the necessity of monitoring TIA at early stage [8].

The main symptom of TIA is that the patient suddenly falling down due to the weakness of both legs, accompanied by vertigo or vomiting, especially when he suddenly gets up after sitting or lying for a long time [9]. For patients with TIA, early treatment should be given to quickly rule out bleeding in the brain or seizures.

At present, various advanced methods and technologies have been used in the diseases prediction and healthcare fields, including acceleration sensors [10], cameras [11], Multiple GPUs [12], Accounting for Label Uncertainty in Machine Learning [13], machine intelligence [14], mobile healthcare framework [15], deep learning approach [16], system in Internet of Medical Things [17], predictive analytics [18] and cloud computing environment [19]. All these significant contributions show their advantage and great usefulness.

In this work, the authors develop a wireless sensing platform (WSP), which is composed of a transmitter and a receiver and this platform also has its unique advantage. It can be installed indoors without any contact with patients. The working process of the WSP is as follows: the transmitter transmits the electromagnetic wave in the C band, the receiver receives the wireless signal and simultaneously extracts the wireless channel state information (CSI) data and saves them. Firstly, we conducted a series of preprocessing on the collected CSI data, including removal of outliers and signal denoising, and then used principal component analysis (PCA) to reduce the dimensionality of the preprocessed data [20]. Finally, two machine learning algorithms, support vector machine (SVM) and random forest (RF) [21, 22], were used to classify, so as to monitor TIA. The experimental results in this paper show that the accuracy of the two machine learning algorithms can reach over 95%, which proves that the method described in this paper can effectively monitor TIA, so as to reduce the life risk of the elderly living alone.

The contributions of this paper are as follows:

1. It is proposed for the first time to monitor TIA by using C-band wireless sensing technology, which avoids the additional burden of wearable devices of monitored objects and does not invade their privacy;
2. Two kinds of machine learning algorithms are used to train the prediction model to increase the stability and accuracy of the prediction results;
3. Our self-developed WSP has the advantages of low cost, convenient and fast.

The rest of the paper is arranged as follows. In the second part, we will introduce the principle of C-Band wireless sensing technology in detail, and the third part will describe the experimental scheme. In the fourth part, we will preprocess the experimental data and classify them by the machine learning algorithms. Experimental results will be discussed in the fifth part, and finally, we summarize the article in the sixth part.

Principle of C-band wireless sensing technology

Wireless signal propagation model

C band has been included in the official document of the Ministry of Industry and Information Technology of the People's Republic of China; in addition, the usage of this band is also recommended by the microwave stations within the Chinese territory. C-Band wireless signal has the characteristics of light like scattering and line-of-sight (LOS) propagation. In the process of propagation, it is easy to be interfered with space environment and appear fading, so that the electromagnetic wave propagating in different paths shows different amplitudes and phases at the receiving end, resulting in multipath effect [23]. The indoor propagation model of C-Band signal is shown in Fig. 1.

According to Fries transfer formula [24], the power of the receiving antenna can be expressed as:

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi R)^2} \tag{1}$$

where P_t, P_r are the power of transmitting antenna and receiving antenna respectively. G_t, G_r are the gain of transmitting antenna and receiving antenna respectively, λ is the wavelength of wireless signal, and R is the distance between the two antennas.

According to Fig. 1, we assume that the distance of the wireless signal reflected through the ceiling and the ground is D, and the distance scattered by the human body is H, then (1) can be rewritten as:

$$P_r = \frac{P_t G_t G_r \lambda^2}{16\pi^2 (R + D + H)^2} \tag{2}$$

According to (2), when there is no moving object on the signal transmission path, R, D and H remain unchanged, and the power of the receiving antenna P_r is stable. When an object moves in the path of signal transmission, H will change, resulting in a change in the received power, that is, the amplitude and phase of the received signal will change. The different amplitude and phase of the received signal contains rich information about the external environment. By processing of the received signal, we

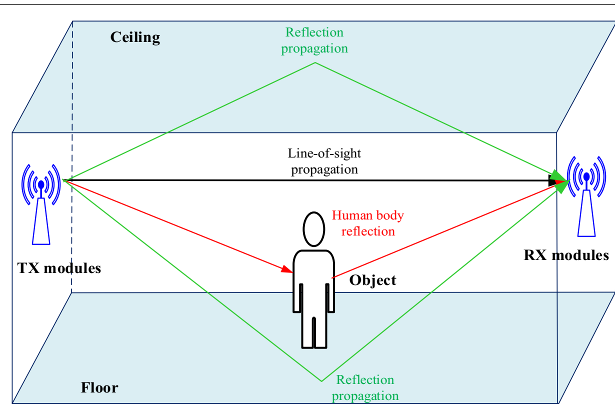

Fig. 1 Wireless signal propagation model for indoor environment

can extract the change information of the external environment from the received signal, so as to achieve the purpose of monitoring.

Channel information

The C-Band WSP used in this paper adopts orthogonal frequency division multiplexing (OFDM) technology at the transmitter. The main advantage of this technology is to improve the data transmission efficiency and spectrum utilization, and it has a good anti-multipath attenuation capability [25]. The platform includes: spectrum analyzer, RF generator, Cables, vector network analyzer, antennas, absorbing material, networked computer, etc.

OFDM technology supports multi-antenna access. If MIMO-OFDM system has N_T (at least 2) antennas at the transmitter and N_R (at least 2) antennas at the receiver, the number of OFDM subcarriers is N_C, then the channel model of wireless system can be expressed as [26],

$$Y = \boldsymbol{H}X + N \tag{3}$$

where Y represents received signal, X represents transmitted signal, N represents ambient noise, $\boldsymbol{H}$ represents the wireless channel state matrix, and its dimension is $N_T \times N_R \times N_C$, as shown below,

$$H = \begin{bmatrix} H_{11} & H_{12} & \dots & H_{1N_R} \\ H_{21} & H_{22} & \dots & H_{2N_R} \\ \vdots & \vdots & \dots & \vdots \\ H_{N_T1} & H_{N_T2} & \dots & H_{N_TN_R} \end{bmatrix}. \tag{4}$$

In the formula above,

$$H_{ij} = \left[H_1(f_1), H_2(f_2), \ldots, H_{N_C}(f_{N_C})\right]. \tag{5}$$

where f_k represents the center frequency of the Kth subcarrier, and $H_k(f_k)(1 \le k \le N_C)$ represents the frequency response of each subcarrier, which can be rewritten as,

$$H_k(f_k) = H_k(f_k)\, e^{jarg(H_k(f_k))} \tag{6}$$

where $H_k(f_k)$ represents CSI amplitude of the Kth subcarrier, and $arg(H_k(f_k)$ represents CSI phase of the Kth subcarrier.

The received signal is continuously sampled in a certain period of time. Through channel estimation [27], a series of discrete $\widehat{H}$ matrices are obtained. Thus, the CSI data we need is obtained. The channel estimation formula is as follows,

$$\widehat{H} \approx \frac{Y}{X} \tag{7}$$

The experimental scheme

It can be seen from the first section that the obvious symptom of TIA is that the patient suddenly falls down due to weakness of both legs. We need to distinguish TIA from other normal daily actions. In this experiment, we will collect data of several actions as shown in Table 1.

Table 1 Daily actions and TIA in the experiment

No	Action
1	Standing
2	Sitting
3	Lying
4	Stand up
5	Sit down
6	Walk
7	TIA

Before the experiment, all the subjects were informed about the matters needing attention, on the other hand, all the subjects were trained, rigorously, about the TIA movements simulation. The experiment was carried out in an approximate ward environment. The size of the laboratory is 7×5 m. The transmitter and the receiver of WSP are placed at both ends of the room, respectively. The object makes the actions shown in Table 1 in the room. The experimental scene is similar to Fig. 1, and the actual experimental scene has sofa, bookcase and other furniture. Absorbing material will reduce the signal reflection and thus the non-line-of-sight propagation would be affected. However, in actual application scenarios, absorbing material is seldomly used, leading to the fact that the multipath propagation has to be taken into account. Due to the fact that single subject was considered, monopole antennas were used in the experiment. They transmit and receive omnidirectional EM waves and easy to design; more complicated directional antennas can be used for some other special environments.

The experimental flow is shown in Fig. 2.

In Fig. 2, the WSP is a self-designed device for monitoring TIA, which is composed of a transmitter, a receiver and a data processing module. The transmitter works in C-Band and adopts OFDM technology. The transmitting signal bandwidth is 40 MHz and there are 30 subcarriers in total. At the same time, the time window is 5 s. The receiver receives the signal, calculates the channel state matrix, and obtains the CSI data. The data processing module first processes the CSI data, and then classifies the indoor human activities through the model trained by the machine learning algorithm, so as to achieve the purpose of monitoring. The platform is a non-contact monitoring tool, which can be directly installed indoors, very safe and convenient.

We collected 300 samples for each action. The waveform of TIA original data collected in the experiment is shown in Fig. 3.

From Fig. 3, we can see that the waveform contains a lot of burrs (noise), which need to be processed. Next, we will describe how to process the data.

The data processing

This section details the data processing approach as shown in Fig. 2.

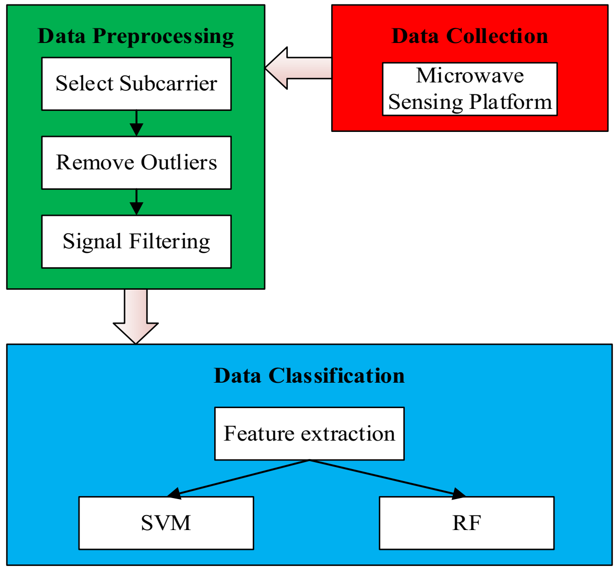

Fig. 2 The experiment flow chart

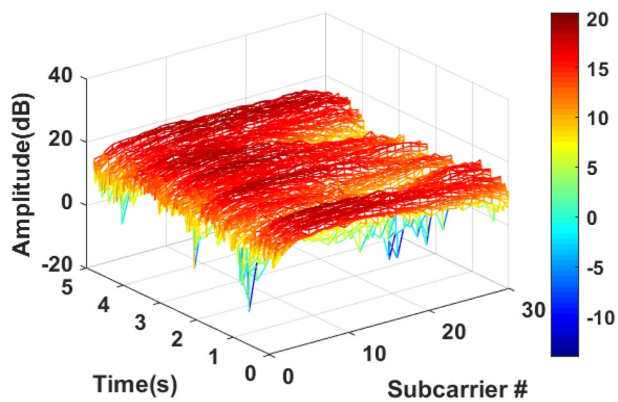

Fig. 3 The waveform of TIA original data

Data preprocessing

Select subcarrier

In order to eliminate redundant information and facilitate subsequent data processing, we need to pick out the appropriate subcarriers. We calculate the variance of 30 subcarriers of each group of data separately. According to the principle, the larger the variance, the larger the amount of information [28], the sequence number of subcarriers selected for each action is shown in Table 2.

Table 2 Selected subcarrier number for each action

Action	Number of subcarriers
Standing	13
Sitting	13
Lying	13
Stand up	16
Sit down	14
Walk	30
TIA	11

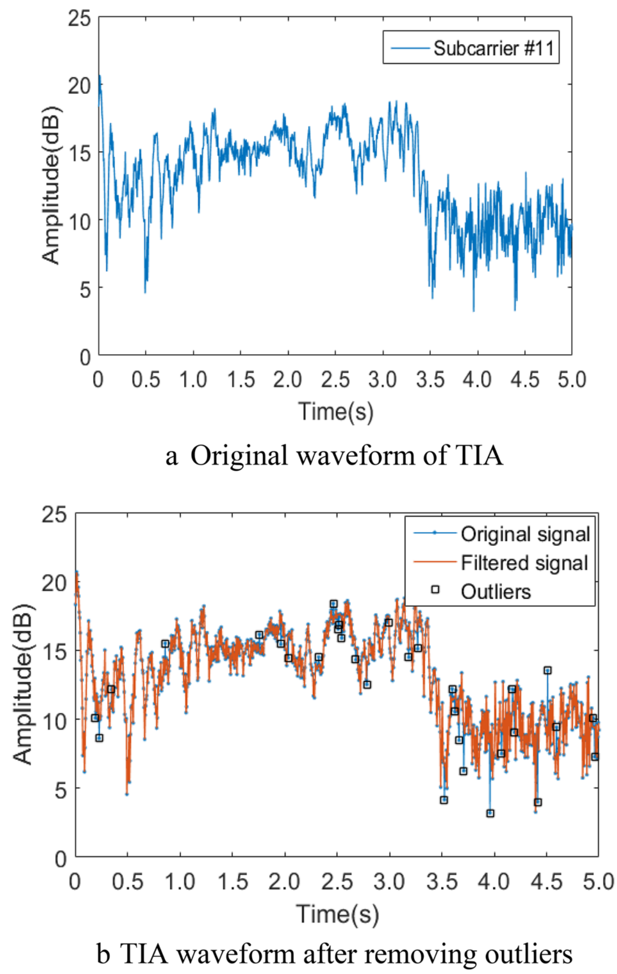

Fig. 4 TIA No.11 subcarrier waveform. **a** Original waveform of TIA. **b** TIA waveform after removing outliers

Remove outliers

The fluctuation of equipment voltage or other factors will cause outliers, which will affect the subsequent data processing. We will remove the outliers according to the Pauta criterion [29]. The original waveform of the TIA is shown in Fig. 4a, after removing the outliers, the waveform is shown in Fig. 4b.

Signal filtering

Before feature extraction, we need to denoise the signal. In this paper, a wavelet transform is used to filter out the signal noise [30], which is mainly based on the following considerations: (1) wavelet transform has good time–frequency characteristics; (2) wavelet transform can well describe the non-stationary characteristics of the signal; (3) wavelet basis function selection is relatively flexible.

In this paper, the signal is decomposed into five layers using the "sym8" wavelet. The Symlet wavelet function is an approximate symmetric wavelet function proposed by Ingrid Daubechies, which is an improvement on the dB function. SimN (N = 2,3,…,8) wavelet has good symmetry, which can reduce the phase distortion of signal analysis and reconstruction to some extent [31]. The waveforms of the motion after the wavelet transform filtering process are shown in Fig. 5. It can be clearly seen from Fig. 5 that the signal waveform is clear and smooth.

Data classification

Feature extraction

Due to the large dimension of data, we will use PCA to reduce the dimension and extract features. In 1901, K. Pearson proposed PCA. The idea of this method is to extract a set of new features that are not related to each other from old features. The new features are arranged in descending order of importance [32].

The principle of PCA is as follows,

$$Y = \boldsymbol{A}X \tag{8}$$

where, $X = (x_1, x_2, \ldots, x_n)$ is the vector in the original n-dimensional feature space, $Y = \left(y_1, y_2, \ldots, y_n\right)$ is a vector composed of n new features, and $\boldsymbol{A}$ is an orthogonal transformation matrix. The new features can be expressed as follows,

$$y_i = \sum_{j=1}^{n} a_{ij} x_j = \boldsymbol{a}_i^T x_j (i = 1, 2, \ldots n) \tag{9}$$

The larger the variance of the new feature, the greater difference in the feature of the sample, and this feature is more important. The variance of each new feature is:

$$var\left(y_i\right) = E\left[y_i^2\right] - E[y_i]^2. \tag{10}$$

E[] is a mathematical expectation, combined with (2), (3) can be reduced to

$$var\left(y_i\right) = \boldsymbol{a}_i^T \boldsymbol{\Sigma} \boldsymbol{a}_i \tag{11}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix of the original eigenvector X, which can be estimated and calculated with samples. Because $\boldsymbol{A}$ is an orthogonal matrix, so $\boldsymbol{a}_i^T \boldsymbol{a}_i = 1$. Using Lagrange method, we can get the maximum variance value as follows,

$$f(\boldsymbol{a}_i) = \boldsymbol{a}_i^T \boldsymbol{\Sigma} \boldsymbol{a}_i - \lambda\left(\boldsymbol{a}_i^T \boldsymbol{a}_i - 1\right) \tag{12}$$

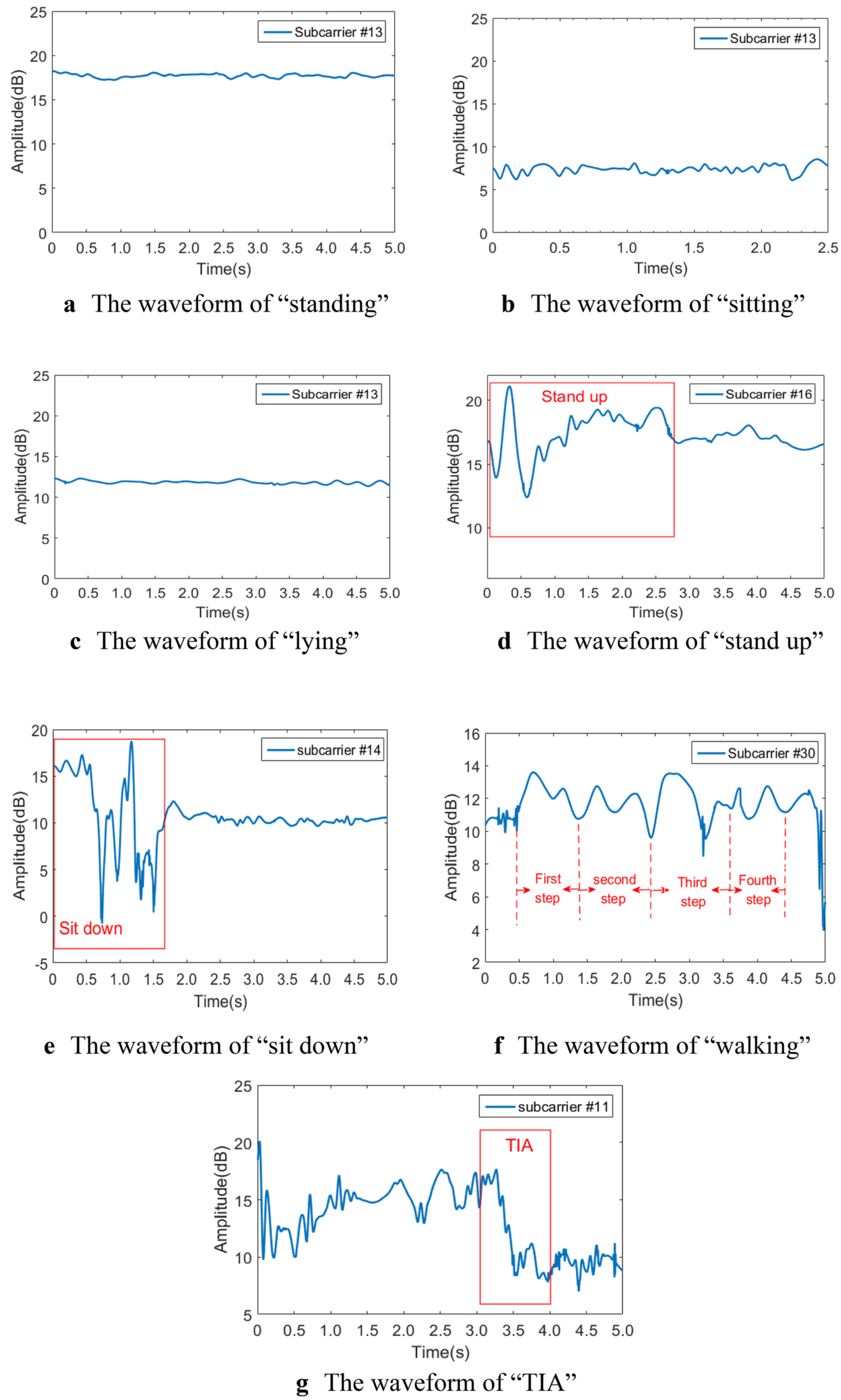

Fig. 5 Waveform of each action after denoising. **a** The waveform of "standing". **b** The waveform of "sitting". **c** The waveform of "lying". **d** The waveform of "stand up". **e** The waveform of "sit down" . **f** The waveform of "walking". **g** The waveform of "TIA"

where λ is the Lagrange multiplier, and the derivative of (5) for $\boldsymbol{a}_i$ is obtained as follows,

$$\boldsymbol{\Sigma}\boldsymbol{a}_i = \lambda\boldsymbol{a}_i \tag{13}$$

Substituting (13) into (11), we can get

$$var\left(y_i\right) = \boldsymbol{a}_i^T\boldsymbol{\Sigma}\boldsymbol{a}_i = \lambda\boldsymbol{a}_i^T\boldsymbol{a}_i = \lambda \tag{14}$$

Combining (13) and (14), the optimal $\boldsymbol{a}_i$ should be the eigenvector corresponding to the maximum eigenvalue of $\boldsymbol{\Sigma}$, and the corresponding y_i is the first principal component, with the largest variance. The covariance matrix $\boldsymbol{\Sigma}$ has a total of n eigenvalues, sorting them from large to small, and then obtaining the second principal component,..., the nth principal component. Thus, the corresponding $\boldsymbol{a}_i$ is obtained, and then the orthogonal transformation matrix $\boldsymbol{A}$ is obtained.

The proportion of information represented by the first k principal components is:

$$P = \sum_{i=1}^{k}\lambda_i/\sum_{i=1}^{n}\lambda_i \tag{15}$$

As a rule of thumb, most of the information in the data is concentrated on a few principal components. As shown in Fig. 6, we selected the first 53 principal components.

Training model

In this paper, SVM and RF are used to classify the data respectively. The basic idea of SVM is to transform the original nonlinear problems in low-dimensional space into linear classification problems in high-dimensional space through feature transformation. This feature transformation is realized by defining appropriate inner product kernel functions. SVM implements different forms of nonlinear classifiers by using different kernel functions, whose performance depends on the selection of kernel functions and the parameter setting of kernel functions. The commonly used kernel functions are: (1) radial basis function; (2) polynomial function; (3) Sigmoid function. Since the linear function can only deal with the linear classification problem and the performance of the

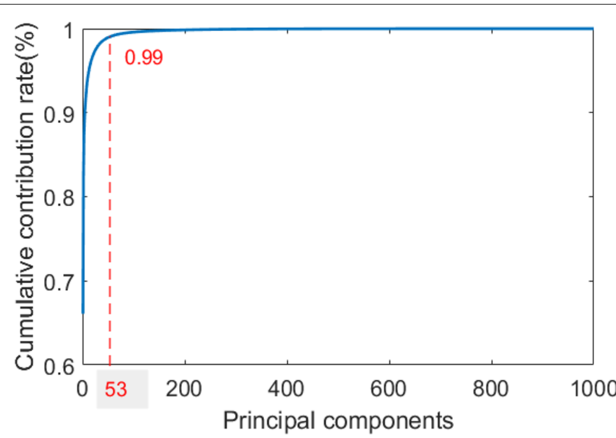

Fig. 6 Principal component cumulative contribution rate curve

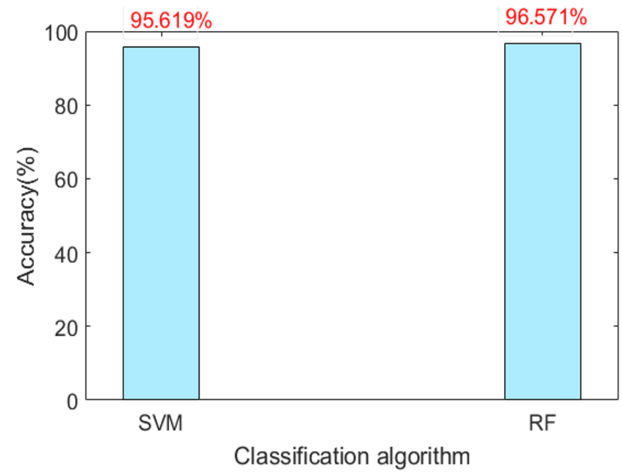

Fig. 7 Precision comparison of two algorithms

Sigmoid function can be obtained by taking a certain parameter of the radial basis function, the radial basis function will be adopted in this paper [21] [33]. The advantages of SVM include high precision, good theoretical guarantees on the overfitting, etc.

The idea of RF is to build many decision trees to form a "forest" and make decisions by voting. Both theoretical and experimental studies show that this method can effectively improve the accuracy of classification [22]. The RF in this paper has 500 decision trees. The advantages of RF include: the resistance to over fitting, stability, etc. It is also worth mentioning that some other advanced machine learning approaches have also been used in the various healthcare and Internet of Things applications [34–40], which also indicate the path of future research.

Results and discussion

The experimental results

The confusion matrix of the results processed by the classification algorithm is shown in Table 3. The total number of samples for each action is 300, 225 samples are taken as the training set and 75 samples are taken as the test set.

Discussion

1. As shown in Table 3, the accuracy of both SVM and RF is over 95%, and the errors mainly come from static actions (standing, sitting and lying). This result can effectively prove the feasibility and reliability of the method described in this paper.
2. From Table 3, we can also see that if only TIA and other actions are distinguished, the accuracy of SVM will reach 97.3%, and the accuracy of RF will reach 98.7%.
3. It can be seen from Fig. 5a, b and c that the amplitude of static action oscillogram is very gentle, and the differentiation is more obvious than other actions. At the same time, it can be seen from Table 3 that static actions are only internal classification deviation, and other actions will not be misjudged as static actions, and static actions

Table 3 Confusion matrix of different classification algorithms

Classification algorithm	Actual action	Predict action (Number of samples)						
		Standing	Sitting	Lying	Stand up	Sit down	Walk	TIA
SVM	Standing	74	0	1	0	0	0	0
	Sitting	0	65	10	0	0	0	0
	Lying	0	7	68	0	0	0	0
	Stand up	0	0	0	75	0	0	0
	Sit down	0	0	0	0	72	0	3
	Walk	0	0	0	0	0	75	0
	TIA	0	0	0	0	2	0	73
RF	Standing	75	0	0	0	0	0	0
	Sitting	0	70	5	0	0	0	0
	Lying	0	8	67	0	0	0	0
	Stand up	0	0	0	74	1	0	0
	Sit down	0	0	0	1	72	0	2
	Walk	0	0	0	0	0	75	0
	TIA	0	0	0	0	1	0	74

The accuracy of two algorithms is shown in Fig. 7

will not be misjudged as other actions. At the same time, the accuracy of walking is 100% in both classification algorithms.

4. It can be seen from Fig. 5 d–g that the oscillogram of stand up, sit down, walk and TIA all have their own characteristics. However, due to the similarity between sit down and TIA, there will be some errors between them. From Table 3, it can be seen that there are one or two sample classification errors in sit down and TIA.
5. In this paper, the accuracy of the RF algorithm is higher than that of the SVM algorithm., so RF is more suitable algorithm for monitoring of TIA.

All the important abbreviations are summarized in the following table:

Conclusion

Monitoring TIA can make patients get timely treatment, which is helpful to prevent patients from subsequent stroke. As far as we know, this paper is the first time to use C-Band wireless sensing technology to monitor TIA in a non-contact way. Firstly, we remove the outliers from the data, filter the data by wavelet transform, then reduce the dimension of the preprocessed data by PCA, and finally train the model by SVM and RF. The accuracy of SVM and RF approaches are 97.3% and 98.7%, respectively; demonstrating the effectiveness of the technology presented in the paper. Next, we further explore the applications of C-Band wireless sensing technology in medical care, and propose more reliable, safe and convenient technical application programs; the main contribution and novelty of the work lies in the development of the platform and the non-contact disease warning in the early stage.

Abbreviations

TIA: Transient ischemic attack; PCA: Principle component analysis; SVM: Support vector machine; RF: Random forest; IoT: Internet of things; WCSI: Wireless channel state information; LoS: Line of sight; OFDM: Orthogonal frequency division multiplexing; MIMO: Multi-input multi-output; RBF: Radial basis function.

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Authors' contributions
Idea QZ, original manuscript QZ and XZ, editing and guidance YL and FT, Funding XY, project management XY. All authors read and approved the final manuscript.

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Availability of data and materials
The data were collected by specialized facilities and platforms.

Competing interests
There are no Competing interests for this manuscript.

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